***Original Research Article***

# Assessment of urban sprawl, land use and land cover changes in Voi town, Kenya using remote sensing and landscape metrics

## ABSTRACT

Rapid and uncontrolled urbanization has become a major concern in both developing and developed countries. Uncontrolled urbanization has led to unplanned increase of residential and commercial areas, informal settlements, housing deficits, uncoordinated and unplanned land use. Understanding and quantifying the spatio-temporal patterns of urban sprawl is critical to inform development of appropriate policies for effective and sustainable land use management.

This study assesses the changes in urban land use/ land cover (LULC) of Voi town between 1999 and 2019 using image classification and spatial metrics. Supervised maximum likelihood classification mapped the LULC using Landsat Thematic Mapper (TM), Landsat Enhanced Thematic Mapper Plus (ETM+) and Landsat Operational Land Imager (OLI) datasets. Post classification approach was used to detect and assess LULC changes, while selected spatial metric indices quantified urban sprawl in the study area.

Change detection analysis results indicated that Voi has been growing rapidly with an urban expansion of 187.96 % from 1999 to 2011; 183.40 % from 2011 to 2019 and 716.1% from 1999 to 2019. The built-up area covered 1.29% of the whole study area in 1999, 3.72% in 2011 and 10.53% in the year 2019. From spatial metrics analysis, the number of built-up area patches were 154, 278 and 526 for the years 1999, 2011 and 2019 respectively. An increase in the number of patches indicated fragmentation and emerging of new built-up areas.

Therefore, city planners need prior planning and further implementation to cope with future rapid and unprecedented growth of the city.

*Keywords: land use/ land cover ;supervised classification ; change detection ; spatial metrics*



## 1. INTRODUCTION

The rapid growth of urban areas accross the world has significantly transformed its society [1]. According to the UN statistics 55% of the world's population reside in urbanized settings and projected that by 2050, the number is predicted to increase to about 65% which is approximately two-thirds of the population in the world [2]. However, as much as urban areas are experiencing a very fast growth rate, cities still occupy approximately 2% of the total land in the world [3]. A report by World Population Prospects, 2019, estimated the population of Africa to increase from 1.3 billion to 4.3 billion between the year 2020 and 2100, with major increases coming from Sub-Saharan Africa (SSA). Based on the 2019 Kenya census figures, the population of Kenya was about 47.5 million and rapid population growth is anticipated [4]. [5] pointed factors leading to urban growth to include increase of population in urban areas, migration from rural to urban areas and conversion of rural settlements into towns or cities by increased and improved infrastructure. [6] reported that the final consequences of this urbanization process is inevitable spatial extension of cities beyond their limits and into the outskirts so as to accommodate the growing urban population. One of the major challenges affecting urban areas is development of informal settlements [7]. These increased informal settlements have been a challenge to planners mostly in developing countries; thus resulting in the adoption of the Sustainable Development Goals (SDGs) especially the eleventh which capitalizes on sustainable growth of formal and informal settlements to ensure cities sustainability [3,8]. It is necessary to assess LULC changes in a certain period of time for sound land use management policies and strategies [9]. Current technologies such as geographical information systems (GIS) and remote sensing (RS) provide a cost effective and accurate tool for understanding the dynamics of landscape [1]. Some extensive research efforts have been made by international scholars to quantify urban patterns and address the challenges of urban LULC [10-14]. Some of the LULC challenges identified in urban areas include uncontrolled growth which has resulted to issues like urban sprawl, environmental pollution, inadequate water supply, insufficient electricity, poor housing, poor drainage and sewage system, garbage disposal and other associated problems [15,16]. In order to understand the urban process, incorporation of landscape metrics to the use of RS is necessary[17,18]. Spatial metrics tool is useful usin describing urban built-up quantitatively and comparing the results using multi-date thematic maps [19]. These metrics allow a significant understanding of the characteristics of the urban landscape for sustainable management of urban environments [20]. Some extensive research efforts have been made on using landscape metrics to measure and assess urban patterns in various landscapes. [21] used twenty two spatial metrics to describe the spatial characteristics of land cover objects in Santa Barbara South Coast. The study concluded that a combination of RS and spatial metrics provides an efficient method for analysis of urban growth patterns. [22] carried out a study to evaluate the change of urban growth and land policies that caused this change in Ankara, Turkey. Their result showed that between 1984 and 2018 the amount of urban land increased from 1.95% to 7.49% of the total area. These results are a clear indication that the proportion of the urban footprint in the landscape in Ankara has increased. [19] performed a spatiotemporal analysis of urban growth patterns in Howrah City, India using temporal RS data and spatial metrics. The study used eight spatial metrics namely; Class Area (CA), Number of Patches (NP), Patch Density (PD), Edge Density (ED), Largest Patch Index (LPI), Area-Weighted Mean Patch Fractal Density (AWMPFD), Contagion (CONTAG) and Shannon's Diversity Index (SHDI). The results of the study showed a progressive growth of the urban built-up areas in and around Howrah City from 1996 to 2016. Using the spatial metrics selected, the identified urban growth types included; infilling, edge expansion and outlying growth. [23] assessed the forest fragmentation of Chitteri Hills in Eastern Ghats using the Fragstat 4.0 software for different classes using specific metrics. The study concluded that monitoring the spatial metrics for forest ecosystems helps in analyzing the change in composition and configuration of the ecosystem. Spatial metrics is a vital tool in forest management for biodiversity conservation and sustainable forest management. It provides information used in determining and evaluating LULC and direction of the urban growth pattern [24]. This study aimed at integrating the use of spatial metrics and RS to examine urban growth patterns and LULC dynamics in Voi town.

## 2. METHODOLOGY

### 2.1 Study Area

Voi is a historical town in Taita Taveta County, which attained a township status in 1932. It lies at latitude 3°23'45.78"S, longitude 38° 33' 21.92"E , at 600m asl and covers an area of

55.31km$^2$. Several forms of infrastructure such as Kenya–Uganda railway, Standard-gauge railway (SGR), airstrips, Voi – Tanzania highway and Mombasa–Nairobi highway, accounts for the rapid growth of the town. The town has proximity to plains utilized as ranching, national parks and mining activities. As a commercial and tourist centre, Voi has attracted a large population from the surrounding areas and it accounts for the highest growth rate of population among the towns in Taita Taveta County.

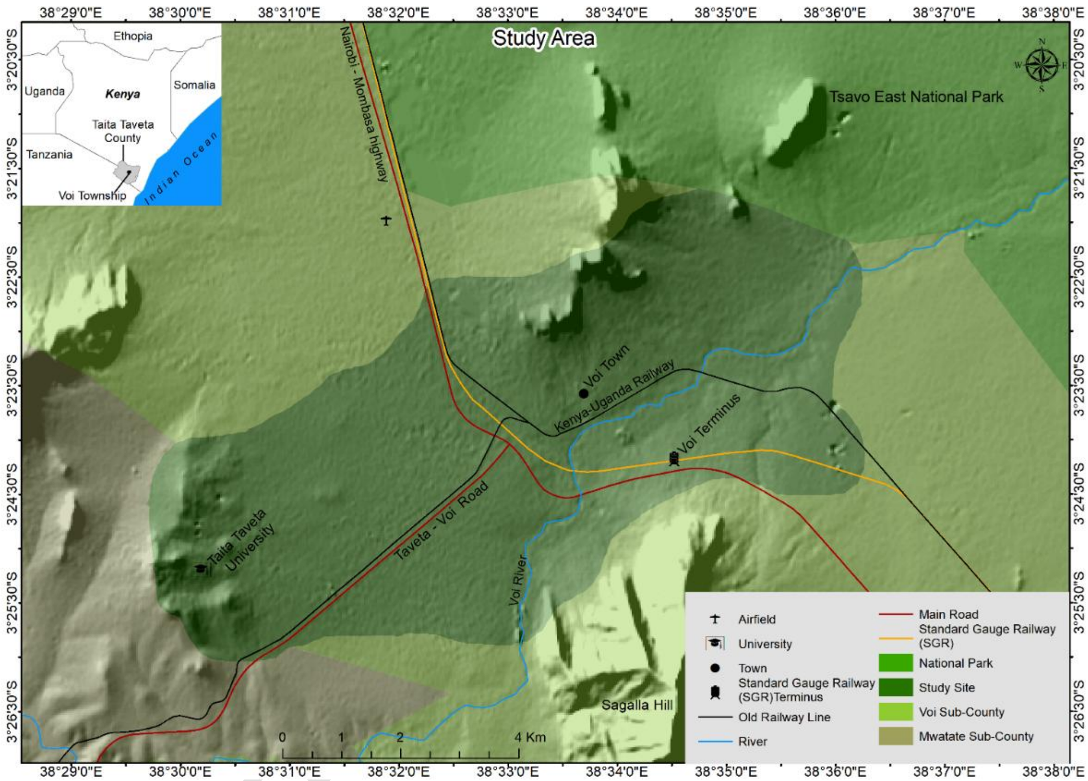


**Fig. 1. Study Area of Voi Town**

Voi town commenced as a settlement location in 1897 when the railway line between Kenya and Uganda reached the town, making it a resting place for the workers; however, a substantial amount of growth was seen between the 1999 and 2009 census as seen in the table below. The population in Voi multiplied from 16,273 in 1989 to 52,472 in 2019 [4,25-27].

**Table 1. Population of Voi town from 1989-2019** [4,25-27]

| Year | Population | % Increase |
|---|---|---|
| 1989 | 16,273 | - |
| 1999 | 24,040 | 47.7 |
| 2009 | 45,483 | 89.2 |
| 2019 | 52,472 | 15 |

## 2.2 Image Pre-processing

Three images captured after the rainy season were obtained from the U.S. Geological Survey (USGS) for use in this study. Landsat 7 ETM+ image (October 1999), Landsat 5 TM image (July 2011) and Landsat 8 (OLI) of July 2019. The remotely sensed data were cropped to the study area and geometrically corrected to the UTM (Universal Transverse Mercator) projection zone 37 south. In order to analyze remotely sensed images, the bands of the individual Landsat images were stacked to create a band set using QGIS 2.18.15 Software to show different combinations of Red Green Blue (RGB) for better interpretation of the land use classes.

## 2.3 Image Classification

To carry out the land use/land cover classification, supervised classification method with maximum likelihood algorithm was applied in the ArcGIS 10.5 Software. The images were classified into three macro-classes namely: built-up, bareland and vegetation cover using maximum likelihood classification algorithm in the supervised classification technique. Water was excluded from the analysis since the study focussed on land areas.

**Table 2. Land cover classification scheme**

| Land use types | Description |
|---|---|
| Built-up | Residential, commercial, industrial, transport networks, Other urban/ built-up land |
| Bare land | Parks, ranches, playground, air strip, grave, mixed barren lands |
| Vegetation Cover | Forest lands, vegetation, grass lands, bushes, sisal plantation |

## 2.4 Accuracy Assessment

After the classification process, the classes were evaluated using independent data. Data accuracy assessment was done by generating randomly selected points and comparing the land cover map generated from classification results to that of ground reference data collected of the same LULC classes [28]. Reference data for accuracy assessment was obtained from GPS field data collected (ground truthing), aerial photographs and topographic maps from the Taita Taveta Planning offices and Google Earth images. Each classified land cover map was compared against the reference data to assess the accuracy of the classification. In assessing the accuracy of the classification, the study used producer's accuracy, user's accuracy, overall accuracy and Kappa coefficient [29-31].

## 2.5 Change Detection

Post classification comparison technique which involves an initial, independent classification of each image, followed by a thematic overlay of the classified maps in ArcGIS software [32] was used.The resultant maps were generated to show the newly built up area between the selected years; 1990 to 2011 and 2011 to 2019 for Voi town.

### 2.4 Quantifying LULC using spatial metrics

The landscape metrics of each map from 1999 to 2019 were calculated. To understand urban LULC in Voi, ten spatial metrics that suited the objectives of the study, were computed using the Patch Analyst extension in ArcGIS, a product of the FRAGSTATS software [33]. The selected metrics were CA, ED, NP, LPI, percentage of landscape (PLAND), landscape shape index (LSI), aggregation index (AI), perimeter-area fractal dimension (PAFRAC) Simpson's diversity index (SIDI), Shannon's evenness index (SHEI).

## 3. RESULTS AND DISCUSSION

### 3.1 Land Use/ Land Cover Change Analysis

The results obtained through the analysis of multi-temporal satellite imageries are illustrated in Fig 2-5

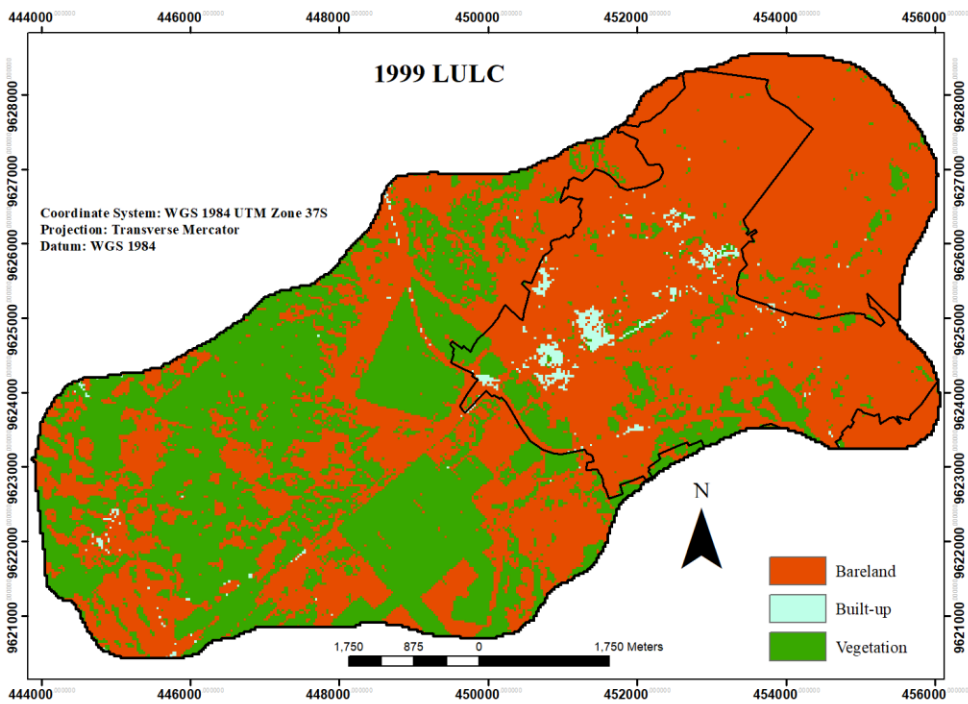


**Fig. 2. Land use/ land cover map of 1999**

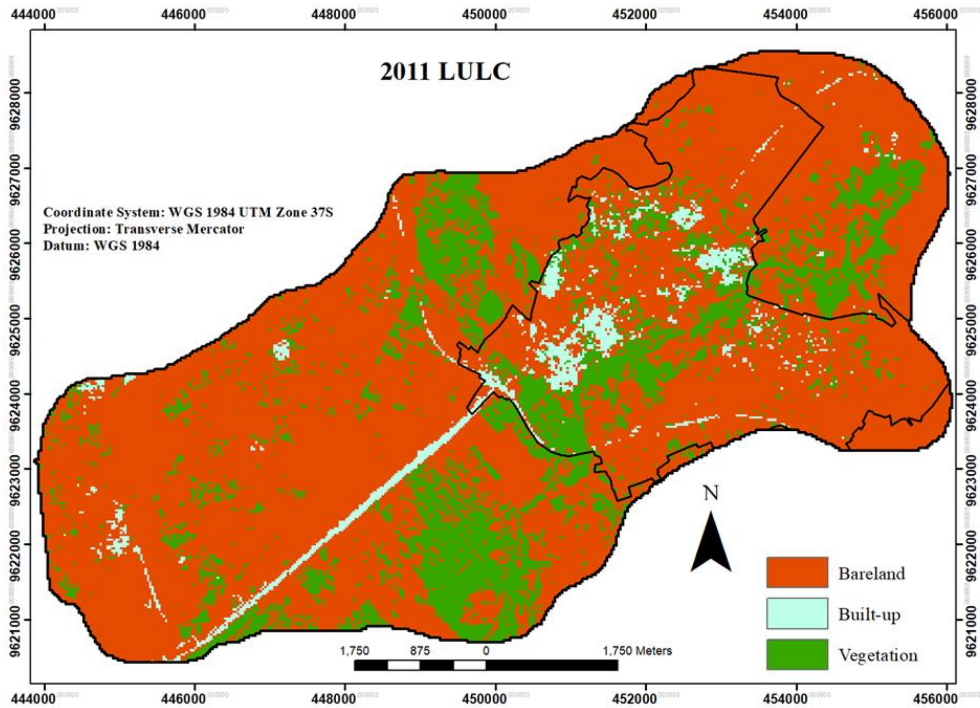

Fig. 3. Land use/ land cover map of 2011

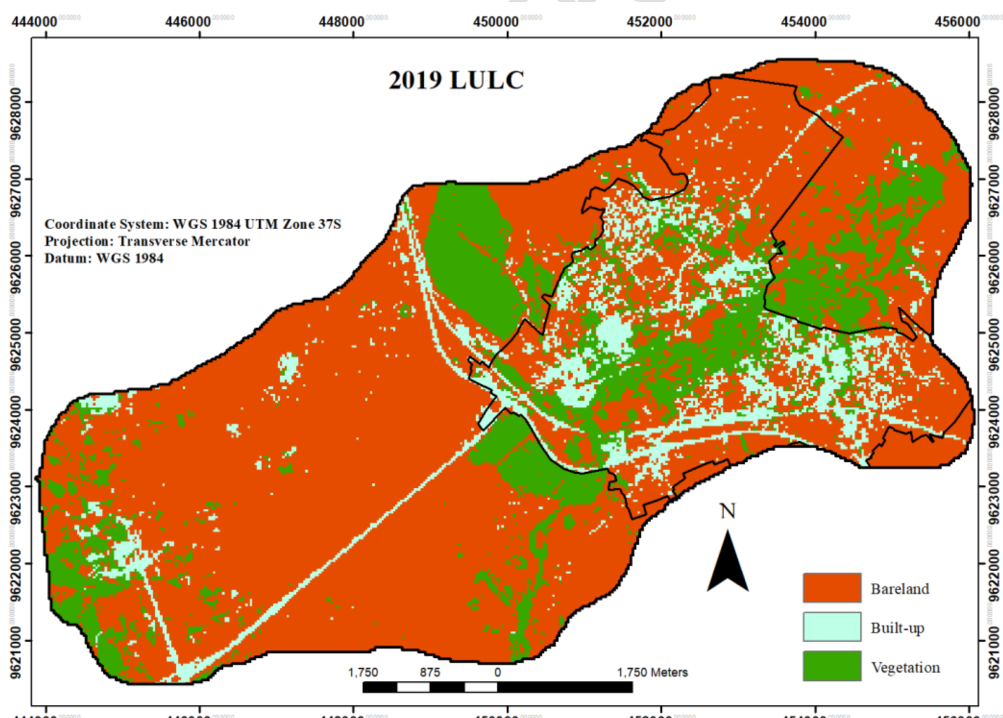

Fig. 4. Land use/ land cover map of 2019

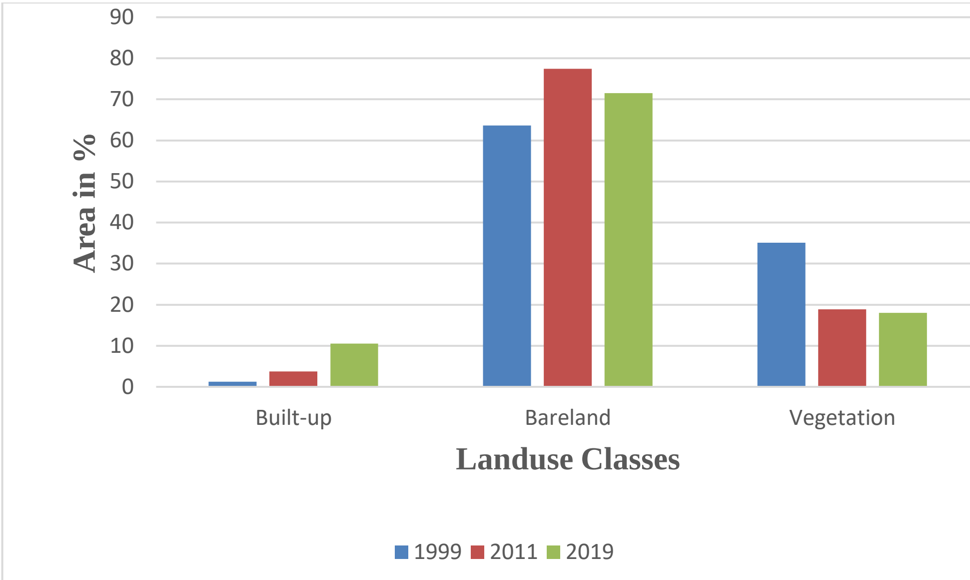


**Fig. 5. Percentage of each land-use types in the landscape from 1999–2019**

The overall data accuracy for the supervised image classification was 81% for 1999, 75% for 2011 and 87% for 2019 respectively; which were within the acceptable limits. According to [34] any accuracy assessment value more than 75% is considered acceptable. Similarly [18] used supervised maximum likelihood classification to classify the Landsat images from 1984 and 2015 into four land use/ land cover classes; and the overall classification accuracy for 1984, 1986, 1991, 1995, 2000, 2006, 2009 and 2015 were 82.3%, 83.4%, 82.5%, 81.6%, 81.7%, 81.3%, 85.7% and 85.8% respectively.The results of the change in LULC are illustrated in Table 3. The result shows that built-up area increased by 187.96 % from 1999–2011, 183.40 % from 2011– 2019 and 716.1% from 1999–2019. Generally, the most change took place in the past twenty years indicating paramount expansion of the city and its surrounding areas. Some of the possible causes of urban sprawl in Voi town include population increase, land tenure and transport and utilities including provision of water and electricity. Population growth which results in increased demand for housing and infrastructure which in turn leads to conversion of more land into urban use. Land tenure causes include unregulated land sales, low land values at the outskirts and speculation that land prices will soon go higher or residential development will reach there sooner. All these result in the easy acquisition of land for building. Lastly, people tend to move to areas with accessible road networks and other forms of transportation. A constant supply of water and electricity is also a pulling factor that causes urban sprawl. Area covered by bare land increased by 21% from 1999–2011 then decreased by 7% from 2011–2019. The reduced percentage of bareland can be attributed to urban expansion where people are utilizing open space to build residential and commercial properties. Vegetation area decreased steadily over the twenty-year study period. This indicate that these two categories are the main contributors to the built-up area. Vegetation areas have decreased primarily due to climatic conditions and development (construction of buildings, roads, and houses).

**Table 3. Change in percent in time series analysis from 1999–2019.**

| **Land-use** | **Change in 1999-2011** | | **Change in 2011-2019** | | **Change in 1999-2019** | |
|---|---|---|---|---|---|---|
| | **Area(ha)** | **%** | **Area(ha)** | **%** | **Area** | **%** |

| | | | | | | |
|---|---|---|---|---|---|---|
| Built-up | 141.93 | 187.96 | 398.79 | 183.40 | 540.72 | 716.1 |
| Bareland | 806.94 | 21.64 | -348.48 | -7.69 | 458.46 | 12.30 |
| Vegetation | -948.87 | -46.20 | -50.31 | -4.55 | -999.18 | -48.65 |

Land use/ land cover changes are complex and interrelated such that a change in a particular land use / land cover type occurs at the expense of another [35]. The results of this study agrees with the results of [36]. Their change detection analysis shows that built-up area increased from 28 to 255 km2 by more than 30% and agricultural land reduced by 33%. In a similar study [37] also recorded a 454% increase in built-up from the year 1978 to 2018 in Ananthapur district of Andhra Pradesh state, South India.

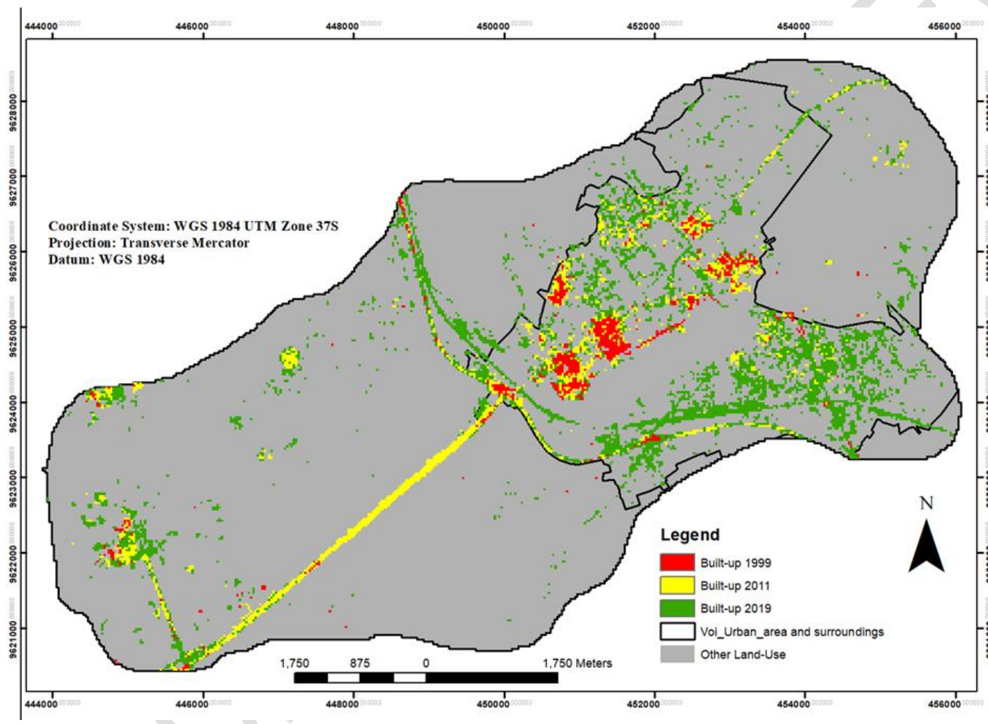


**Fig. 6. Overlaid built-up area of Voi town and its surroundings from 1999–2019**

Fig 6 and 7 are a representation of how Voi town has grown over the 20-year study period. It is clear that the town is expanding outwards and in all directions. Fig 7 shows a zoomed view of linear settlement in the twenty years period as it majorly occurred along the main roads. This is clearly seen along the voi-mwatate road and along the standard gauge railway. Much of these developments have occurred within 2011-2019 period, which has seen major infrastructural improvement in the region. Another sprawl pattern observed is the clustered settlment which is seen in some parts of the town. This kind of pattern is observed due to increased population and growth of the central business district, industries and the taita taveta university around Voi town. With increased population within the period 1999-2019, there is increased concentration of population within Voi town.

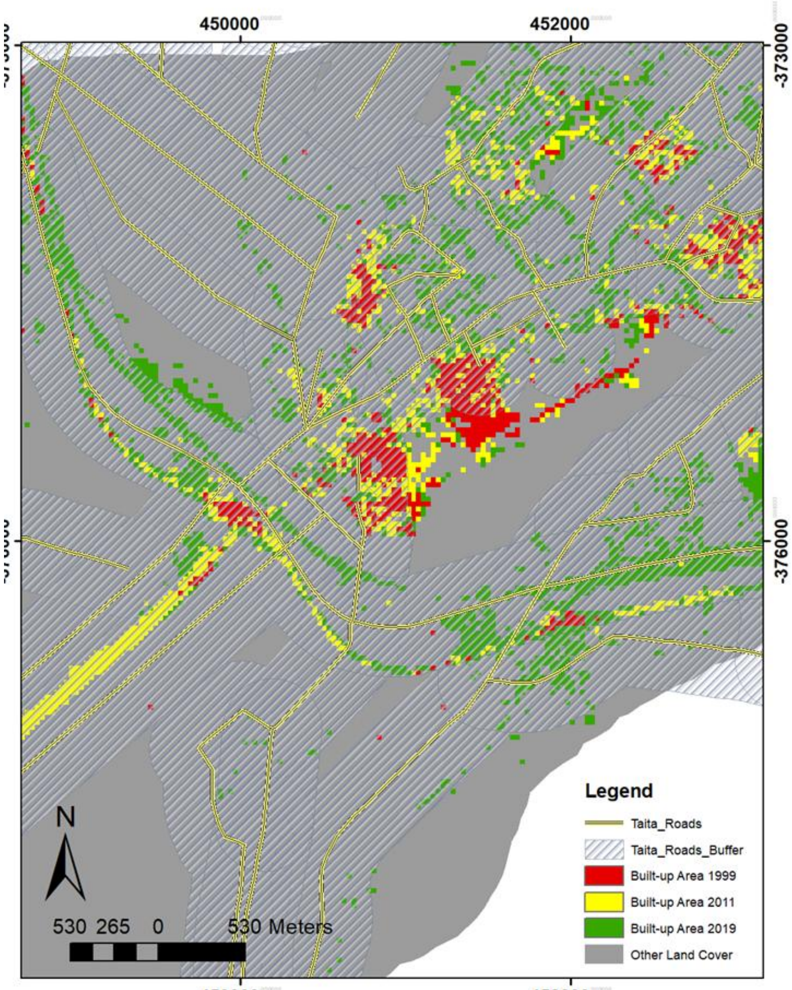


**Fig. 7. Clustered and Linear Sprawl pattern**

### 3.2 Change in urban areas using landscape metrics

Land use / land cover maps for three different years were used to compute spatial metrics for the analysis with FRAGSTATS software. The temporal urban growth patterns of the spatial metrics are illustrated (Table 4). Most of the landscape metrics show a positive trend while a few of these indices show a negative trend. Following the constant urban expansion over the study period; CA, PLAND, NP have increased from 1999 to 2019 which signifies a higher urbanization rate between 2011 and 2019. There was a continuous increase in the NP from 154 in 1999, and increased to 526 in 2019. Similar findings were reported by [38] who recorded an increase in the NP between 1995 and 2015. Contrary to this, there was a reduction in the number of patches due to lower degree of fragmentation of urban patches in Greater Noida in India [39]. In a study in Kathmandu Valley (Nepal) the ED almost doubled in the whole study period [40]. There was an increase in the values of PAFRAC from 1.5135 to 1.5509 from 1999 to 2019 indicating that the urban patches were becoming complex and irregular in shape. There was a decline in PAFRAC in Greater Noida between 1977 and 2011 which indicates that there has not been much change in the shape of built-up area during the study period [39]. Landscape Shape Index (LSI) also increased from 14.4483 to 32.4639 from 1999 to 2019, an indicator that built-up area in 2019 was more dispersed when compared to 1999. This is contrary to the study done in the urban coastal wetland of Yancheng in China where the LSI decreased during the study period [41]. The AI values in this study increased from 51.8519 to 61.3912, demonstrating that the built-up area evolving into an almost single patch. The AI was also used in quantifying and measuring the degree of aggregation or disaggregation in the pattern of urban sprawl. Largest patch index (LPI) displayed an increasing trend from 0.2628, 0.8729 and 2.239 in 1999, 2011 and 2019 respectively which is an indication of the centralization of urban growth. This result is similar to the outcomes of [42] in Kampala City (Uganda) where LPI increased progressively. According to Abebe the LPI increased due to the fact that urban areas were becoming more aggregated and integrated with the urban cores. However,[43] recorded a decline in values of LPI exposing a higher fragmentation of the urban landscape which also indicates the rural landscape dominancy.

**Table 4. Class metrics indices for built-up area from 1999–2019**

| **Years** | **Class Metrics** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **CA** | **PLAND** | **NP** | **LPI** | **ED** | **LSI** | **PAFRAC** | **AI** |
| **1999** | 75.51 | 1.2893 | 154 | 0.2628 | 8.539 | 14.4483 | 1.5135 | 51.8519 |
| **2011** | 217.44 | 3.7127 | 278 | 0.8729 | 20.8788 | 20.6768 | 1.5268 | 58.8422 |
| **2019** | 616.23 | 10.5219 | 526 | 2.239 | 54.9016 | 32.4639 | 1.5509 | 61.3912 |

## 4. CONCLUSION

This study analyzed the LULCC and spatiotemporal pattern of urban growth in Voi using multi-temporal Landsat data,GIS, RS and spatial metrics indices. The results reveal that the major LULC in the study area is bare land and this is due to the fact that Voi is a semi-desert region with an annual rainfall of 733mm. So the most part of the year the area is dry. During the study period, bare land increased by 12.30% (458.46 ha) while vegetation cover decreased by 48.65% (999.18 ha) due to climate influence and clearing of vegetation to create room for settlement. The area under built-up land increased by 716.1 % (540.72 ha) during the study period mainly due to town area expansion. Through the results placed in the tables and the use of spatial metrics, it was clearly shown that there was an increase in urban areas which were clearly illustrated in the land cover maps for the period of 20 years. Thus, the present study indicates that changes in LULC and quantification of spatial phenomena could be detected by use of GIS and RS techniques. The results provides relevant information for urban planners, developers and administrators for future development and policy formulation to ensure sustainability within Voi. Future studies could focus on the driving factors associated with such type of urban growth in Voi and its surroundings.

**COMPETING INTERESTS DISCLAIMER:**

**AUTHORS HAVE DECLARED THAT NO COMPETING INTERESTS EXIST. THE PRODUCTS USED FOR THIS RESEARCH ARE COMMONLY AND PREDOMINANTLY USE PRODUCTS IN OUR AREA OF RESEARCH AND COUNTRY. THERE IS ABSOLUTELY NO CONFLICT OF INTEREST BETWEEN THE AUTHORS AND PRODUCERS OF THE PRODUCTS BECAUSE WE DO NOT INTEND TO USE THESE PRODUCTS AS AN AVENUE FOR ANY LITIGATION BUT FOR THE ADVANCEMENT OF KNOWLEDGE. ALSO, THE RESEARCH WAS NOT FUNDED BY THE PRODUCING COMPANY RATHER IT WAS FUNDED BY PERSONAL EFFORTS OF THE AUTHORS.**

## REFERENCES:

1. Bhat, P. A., ul Shafiq, M., Mir, A. A., & Ahmed, P. (2017). Urban sprawl and its impact on landuse/land cover dynamics of Dehradun City, India. *International Journal of Sustainable Built Environment*, *6*(2), 513-521.

2. DESA, U. (2018). United Nations, Department of Economic and Social Affairs, Population Division. World Population Prospects 2018. *Online Edition. Rev*, *1*.

3. UNHABITAT, 2016. Urbanisation and Development: Emerging Futures. World Cities Report 2016: United Nations Human Settlements Programme.

4. KNBS Kenya National Bureau of Statistics: Kenya National Population and Housing Census 2019. Nairobi: KNBS; 2020

5. BenBella, D. E. (2016). *An Evaluation and Analysis of Urban Expansion of Kampala from 1995 to 2015* (Doctoral dissertation, Southern Illinois University Carbondale).

6. Mosammam, H. M., Nia, J. T., Khani, H., Teymouri, A., & Kazemi, M. (2017). Monitoring land use change and measuring urban sprawl based on its spatial forms: The case of Qom city. *The Egyptian Journal of Remote Sensing and Space Science*, *20*(1), 103-116.

7. Saghir, J., & Santoro, J. (2018). Urbanization in Sub-Saharan Africa. Meeting Challenges by Bridging Stakeholders. *Center for Strategic & International Studies*, (April), 1–7.

8. United Nations, U., 2015. The Millennium Development Goals Report 2015. Department of Economic and Social Affairs, Population Division, United Nations, New York.

9. Getu, K., & Bhat, H. G. (2021). Analysis of spatio-temporal dynamics of urban sprawl and growth pattern using geospatial technologies and landscape metrics in Bahir Dar, Northwest Ethiopia. *Land Use Policy*, *109*, 105676.

10. Aithal, B. H., & Ramachandra, T. V. (2016). Visualization of urban growth pattern in Chennai using geoinformatics and spatial metrics. *Journal of the Indian Society of Remote Sensing*, *44*(4), 617-633.

11. Chakraborti, S., Das, D. N., Sannigrahi, S., & Banerjee, A. (2018). Assessing Dynamism of Urban Built-up Growth and Landuse Change Through Spatial Metrics: A Study on Siliguri and its Surroundings

12. Abass, K., Adanu, S. K., & Gyasi, R. M. (2018). Urban sprawl and land use/land-cover transition probabilities in peri-urban Kumasi, Ghana. *West African Journal of Applied Ecology*, *26*, 118-132.

13. Yiran, G. A. B., Ablo, A. D., Asem, F. E., & Owusu, G. (2020). Urban sprawl in sub-Saharan Africa: A review of the literature in selected countries. *Ghana Journal of Geography*, *12*(1), 1-28.

14. Shao, Z., Sumari, N. S., Portnov, A., Ujoh, F., Musakwa, W., & Mandela, P. J. (2021). Urban sprawl and its impact on sustainable urban development: a combination of remote sensing and social media data. *Geo-spatial Information Science*, *24*(2), 241-255.

15. Jing, Y., Liu, Y., Cai, E., Liu, Y., & Zhang, Y. (2018). Quantifying the spatiality of urban leisure venues in Wuhan, Central China–GIS-based spatial pattern metrics. *Sustainable cities and society*, *40*, 638-647.

16. Yılmaz, M., & Terzi, F. (2021). Measuring the patterns of urban spatial growth of coastal cities in developing countries by geospatial metrics. *Land Use Policy*, *107*, 105487.

17. Abedini, A., Khalili, A., & Asadi, N. (2020). Urban Sprawl Evaluation Using Landscape Metrics and Black-and-White Hypothesis (Case Study: Urmia City). *Journal of the Indian Society of Remote Sensing*, *48*(7), 1021-1034.

18. Magidi, J., & Ahmed, F. (2019). Assessing urban sprawl using remote sensing and landscape metrics: A case study of City of Tshwane, South Africa (1984–2015). *The Egyptian Journal of Remote Sensing and Space Science*, *22*(3), 335-346.

19. Mandal, S., Kundu, S., Halder, S., Bhattacharya, S., & Paul, S. (2020). Monitoring and Measuring the Urban Forms Using Spatial Metrics of Howrah City, India.

20. Terfa, B. K., Chen, N., Liu, D., Zhang, X., & Niyogi, D. (2019). Urban expansion in Ethiopia from 1987 to 2017: Characteristics, spatial patterns, and driving forces. *Sustainability*, *11*(10), 2973.

21. Herold, M., Couclelis, H., & Clarke, K. C. (2005). The role of spatial metrics in the analysis and modeling of urban land use change. *Computers, environment and urban systems*, *29*(4), 369-399.

22. Cengiz, S., Görmüş, S., & Oğuz, D. (2022). Analysis of the urban growth pattern through spatial metrics; Ankara City. *Land Use Policy*, *112*, 105812.

23. Narmada, K., Gogoi, D., & Bhaskaran, G. (2021). Landscape metrics to analyze the forest fragmentation of Chitteri Hills in Eastern Ghats, Tamil Nadu. *Journal of Civil Engineering and Environmental Sciences*, *7*(1), 001-007.

24. Angel, S., Parent, J., & Civco, D. (2007, May). Urban sprawl metrics: an analysis of global urban expansion using GIS. In *Proceedings of ASPRS 2007 Annual Conference, Tampa, Florida May* (Vol. 7, No. 11). Citeseer.

25. KNBS Kenya National Bureau of Statistics: Kenya National Population and Housing Census 2009. Nairobi: KNBS; 2010

26. Republic of Kenya, 2001. 1999 Population and Housing Census Vol. 1 & II. Central Bureau of Statistics & Ministry of Finance and Planning 2001.

27. Republic of Kenya, 1994. Kenya Population Census 1989 Vol. 1. Central Bureau of Statistics , Office of the Vice President & Ministry of Planning and National Development 1994.

28. Dimitrov, P., Olofsson, P., Jelev, G., & Kamenova, I. (2018). Mapping of forest cover change by post-classification comparison and multitemporal classification of spot data–a Bulgarian case study. *Aerospace Research in Bulgaria*, *30*, 42-62.

29. Liping, C., Yujun, S., & Saeed, S. (2018). Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PLoS ONE*, *13*(7). https://doi.org/10.1371/journal.pone.0200493

30. Moghadam, N. K., Delavar, M. R., & Forati, A. (2017). Vegetation monitoring of Mashhad using an object-oriented post classification comparison method. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *42*(4W4), 123–131. https://doi.org/10.5194/isprs-archives-XLII-4-W4-123-2017

31. Tajbakhsh, M., Memarian, H., & Shahrokhi, Y. (2016). Analyzing and modeling urban sprawl and land use changes in a developing city using a CA-Markovian approach. *Autumn 2016 Global J. Environ. Sci. Manage*, *2*(4), 397–410.

32. Almutairi, A., & Warner, T. A. (2010). Change Detection Accuracy and Image Properties : A Study, 1508–1529. https://doi.org/10.3390/rs2061508

33. Berila, A., & Isufi, F. (2021). Two decades (2000–2020) measuring urban sprawl using GIS, RS and landscape metrics: A case study of municipality of Prishtina (Kosovo). *Journal of Ecological Engineering*, *22*(6), 114-125

34. Foody, G. M. (2008). Harshness in image classification accuracy assessment. *International Journal of Remote Sensing*, *29*(11), 3137-3158.

35. Cheruto, M. C., Kauti, M. K., Kisangau, D. P., & Kariuki, P. C. (2016). Assessment of land use and land cover change using GIS and remote sensing techniques: A case study of Makueni County, Kenya.

36. Hegazy, I. R., & Kaloop, M. R. (2015). Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt. *International Journal of Sustainable Built Environment*, *4*(1), 117-124.

37. Vivekananda, G. N., Swathi, R., & Sujith, A. V. L. N. (2021). Multi-temporal image analysis for LULC classification and change detection. *European journal of remote sensing*, *54*(sup2), 189-199.

38. Wan, Y., Deng, C., Wu, T., Jin, R., Chen, P., & Kou, R. (2019). Quantifying the spatial integration patterns of urban agglomerations along an inter-city gradient. *Sustainability (Switzerland)*, *11*(18), 1–22. https://doi.org/10.3390/su11185000

39. Sinha, S. K. (2018). Spatial Metrics : A Tool for Measurement of Urban Growth / Sprawl Spatial Metrics. *Jigyasa*, *11*(3), 974–7648.

40. Thapa, R. B., & Murayama, Y. (2009). Examining spatiotemporal urbanization patterns in Kathmandu Valley, Nepal: Remote sensing and spatial metrics approaches. *Remote Sensing*, *1*(3), 534–556. https://doi.org/10.3390/rs1030534

41. Tian, P., Cao, L., Li, J., Pu, R., Shi, X., Wang, L., ... & Shao, S. (2019). Landscape grain effect in Yancheng coastal wetland and its response to landscape changes. *International Journal of Environmental Research and Public Health*, *16*(12), 2225.

42. Gezahegn Aweke Abebe, (2013). Quantifying Urban Growth Pattern in Developing Countries Using Remote Sensing and Spatial Metrics: A Case Study in Kampala, Uganda. Enschede, 108 pp.

43. Talukdar, S., Eibek, K. U., Akhter, S., Ziaul, S. K., Islam, A. R. M. T., & Mallick, J. (2021). Modeling fragmentation probability of land-use and land-cover using the bagging, random forest and random subspace in the Teesta River Basin, Bangladesh. *Ecological Indicators*, *126*, 107612.